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Impact of probabilistic small-scale photovoltaic generation forecast on energy management systems

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ABSTRACT

Demand-side Management (DSM) algorithms are exposed to several uncertainties due to their dependency on renewable energy generation forecasts. On the large scale, generation and load forecasts can be relatively accurate, yet on the residential scale, forecasting errors increase due to higher uncertainties. One potential solution is to incorporate a probabilistic PV forecast into an optimal DSM algorithm instead of the existing deterministic PV forecasting algorithms. Hence, in this contribution, a numerical analysis that compares the potential of using a probabilistic PV forecast instead of the conventional deterministic algorithms in a DSM algorithm, is presented. Results show that under different household energy system configurations, the DSM algorithm with the probabilistic PV generation forecast leads to an increase in self-sufficiency and self-consumption by 24.2% and 17.7%, respectively, compared to the conventional deterministic algorithms. These results indicate that probabilistic PV forecasting algorithms may indeed have a higher potential compared to the conventional deterministic ones.

1. Introduction

Recent energy policies currently play an influential role in reshaping the electricity grid infrastructure globally. Green energy incentives were introduced over the past 25 years to enable the integration of more renewables, and embrace a low-carbon economy. In Germany, the renewable energy sources act Erneuerbare Energien Gesetz (EEG), was introduced in 2000, along with amendments till 2014 to prioritize the access of renewable energy sources (RES) to the grid (Wüstenhagen and Bilharz, 2006). This act enabled rapid integration of wind energy and photovoltaics (PV) through guaranteeing the supplier an energy purchase at a fixed tariff (Federal Ministry for Economic Affairs and Energy, 2015). Enforcing similar acts, along with the consistent decrease of investment costs in PV systems, led to a boost in the installation of PV systems, especially in the residential sector. In this sector, the installed capacities represents 39.4% of the overall capacities compared to 19.2% for the commercial and industrial sectors (Maron et al., 2011). Consequently, PV integration within the residential sector has become a continuous research topic, with crucial economic implications for single households (Nikmehr et al., 2017).

For these households, electricity bills need to be minimized to reduce the investment costs for the residents (Zhou et al., 2016; Shakeri et al., 2017; Celik et al., 2017). In addition, autonomy and self-consumption need to be considered, yet they are byproducts of cost optimization and electricity bill minimization. Cost optimization is reached via applying demand side management (DSM), through which the loads are shifted and coordinated to maximize the use of the available PV generation within the residential household. Several research projects detailed the type of shiftable loads that could be integrated such as the white goods (e.g. washing machine, dish washer and the tumble dryer), heat pumps, or electrical vehicles [EV] (Lehrstuhl für Energiewirtschaft und Anwendungstechnik; El-Baz et al., 2016; El-Baz and Tzscheutschler, 2014). Others integrated thermal and electrical storages, or a micro combined heat and power cycle (micro-CHP) as an additional in-house energy supply source. All these components are always connected together through an energy management system (EMS), where the DSM strategy is realized. In all such possible configurations, the PV system was a dominant component. Thus, PV generation forecast is necessary for shifting the desired loads to the most suitable time-slot in the future.

Applied DSM strategy performance is highly dependent on the quality of the PV forecast. Hanna et al. (2014) showed the impact of forecast error on battery discharging behavior, where the forecast errors in specific days reached twice to ten times the battery energy capacity and led to a void dispatch schedule. Klingler and Teichtmann (2017) demonstrated the need for a better PV forecasting data for a grid friendly PV + Battery system. At the moment, there is a gap in the research tackling or providing solutions to the small-scale residential

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Nomenclature

$\Lambda(t_t)$	relative difference training variable
λ_i	relative difference of a training set
cc	cloudiness
cc_{high}	high-level cloudiness
cc_{low}	low-level cloudiness
cc_{mid}	mid-level cloudiness
Du_d	device duration
E_f	ded-in energy
E_g	imported energy
e_w	ratio of self-consumption to self-sufficiency
E_{sc}	self-consumed energy
e_{sc}	self-consumption
e_{ss}	self-sufficiency
f	mid-level cloudiness coefficient
$F_i(\lambda_i)$	cumulative distribution of a specific category
G	generation profile
i	training set category
In_d	device interruptibility
j	high-level cloudiness coefficient
k	low-level cloudiness coefficient
L	load profile
O	overlapping profile
Ocr	absolute number of occurrences
P_{ccs}	PV calibrated clear sky power generation
$P_{clearsky}$	PV cleary sky power generation
P_{cs}	PV clear sky power generation
$P_{dailymax}$	PV daily maximum power generation
P_d	device power
P_{f_r}	reference PV forecast power generation
P_m	PV measured power generation
P_m	PV measured power
P_{pccs}	PV clear sky power generation after partial shading detection
P_{pf}	PV point forecast
p_{pp_q}	PV probabilistic forecast curve
P_{pp}	PV probabilistic forecast
Pr_d	device probability of multiple usage
Q	cumulative probability of occurence set
q	specific probability of occurence
t	time
t_f	forecast time horizon
T_n	end of training period
t_t	training time
$wrRMSE$	weighted relative root mean squared error

PV forecast implications on DSM. In other words, no clears answers are presented in the literature addressing and defining the required accuracy for rooftop PV forecast, the variability and uncertainity effect on the DSM in the residential sector, or the forecast type (i.e. probabilistic, or deterministic) required for DSM algorithms in real-life conditions.

1.1. Study objectives

Hence, the objective of this contribution is to provide answers to these questions via analyzing the potential of incorporating a probabilistic forecast instead of a conventional deterministic one in the DSM algorithm. This potential is then analyzed based on defined metrics to demonstrate whether the probabilistic forecast would lead to a different operation plan for the household devices, and whether the new operation plan would lead to a significant increase in self-energy consumption and autonomy of the household. To show the effect of the forecast independently on the operation of the DSM algorithm, a simple algorithm was implemented that can fit to both the probabilistic forecast and the conventional deterministic forecast. In a separate publication (El-Baz et al., submitted for publication), the probabilistic PV-forecast algorithm was detailed, where multiple PV generation curves were produced based on a statistical probabilistic analysis. In this contribution, the impact of such an algorithm on an EMS is presented to evaluate the potential of probabilistic forecast.

This contribution is structured as follows: Section 2 provides a background of the related literature in the field of DSM and PV generation forecasts. Section 3 presents the methodology and metrics used to evaluate the potential of DSM. Section 4 presents the results of a comparison between the potential of DSM under the probabilistic forecast and a conventional reference forecast. Section 5 provides the concluding remarks.

2. Background

2.1. DSM in households

DSM was introduced in the late 1970s (Lampropoulos et al., 2013) to encourage consumers to alter their load to produce a desired load profile for the utility. This means that the customer in this case needs to alter both the magnitude and the time pattern of the load to fit to the utility's plan. Thus, the scope of DSM incorporates several strategies such as peak clipping, valley filling, load shifting, strategic conservation, strategic load growth, and flexible load shaping (Gellings, 1985). The utility encourages the consumers to shift their own loads using financial incentives. Therefore, Real-Time Price (RTP) and Time-of-Use (ToU) tariffs were introduced so that the customers can shift their load from the peak hours to the off-peak hours (Strbac, 2008).

Several theoretical studies and pilot projects investigated the potential of DSM strategies on different scales (Meyabadi and Deihimi, 2017; Finn et al., 2013; Jiang et al., 2017; Gottwalt et al., 2011). To study the impact of DSM on different electricity tariffs, Gottwalt et al. (2011) developed a model to generate household load profiles and simulated them under flat-tariffs and time-based tariffs. The author found that several household loads are available for shifting, which benefit the utility to balance the supply and demand. To simulate real-world factors, Yang and Xia (2017) included in his contribution not only the electricity tariffs, but also the environmental performance and residents' behavior. The authors found that a combination of optimal DSM along with local energy supply sources could significantly reduce the electricity import from the grid and minimize the expenditure. Storage systems such as batteries and heat storages, in addition to the thermal mass of the buildings, also play a major role in enabling the DSM. Shakeri et al. (2017), Arteconi et al. (2017) and Shi et al. (2016) among others used storages to enable shifting and reducing the loads for extended hours depending on the consumer's demand and building type.

Different algorithms were presented in the literature, which applied different techniques such as artificial neural networks (ANN) (Matallanas et al., 2012), stochastic optimization (Galvan-Lopez et al., 2015), mixed-integer nonlinear programming (MINLP) (Yang et al., 2017), or greedy approach (Shi et al., 2016). Along with the variations in the algorithms, the combinations with the PV systems varied. PV along with batteries, EV, or heat pumps were considered. In all these cases, PV forecast was used for the control algorithm to make DSM decisions 6 h, 12 h or 24 h ahead (Matallanas et al., 2012). These algorithms are categorized as open-loop: the DSM strategy defined the optimal plan of the loads in future time-slots based on the current forecast without considering any uncertainties of supplied forecasts.